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Chapter 18 Volatility Transmission across Commodity Futures Markets

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ABSTRACT

The recent sharp movements in crude oil prices and their impact on other commodities have renewed interest in the assessment of dynamic interactions between commodity futures markets. This chapter examines this important topic by investigating the intensity and direction of volatility transmission across three major classes of commodities including agricultural products (corn, coffee, and soybeans), energy (crude oil and gas), and metals (copper, gold, and silver). Overall, the evidence suggests that important volatility episodes and fluctuations exist across major commodity markets; the total cross-market spillovers are limited until the onset of financial crisis of 2007-2008. As the crisis intensified, so too did the commodity volatility spillovers with substantial stress carrying over from the energy and metal markets to others. These findings are important in understanding the level and transmission mechanism of risk across commodity futures markets and are relevance to regulators in formulating effective policies to tackle excessive volatility, particularly during turbulent periods.

INTRODUCTION

In the wake of the financial crisis of 2007-2008, also called the global financial crisis (GFC), interest in the commodity markets soared as many turned to these so-called “alternative investments” to hedge against heightened uncertainty and adverse economic conditions.

Institutional investors started to expand their investable asset universe beyond the traditional asset classes of stocks, bonds, and cash. Commodities have gained greater prominence in recent years. According to The World Bank (2012), investment fund activity in commodities was about \$330 billion as of the first quarter of 2012, which was nine times higher than in the early 2000s, when this activity started becoming a popular investment vehicle within the financial community.

Despite this growing popularity, the recent increased volatility in crude oil prices and the spillover effects on other commodity markets have brought about a renewed concern about excessive fluctuations and volatility spillovers among the global commodity markets. Some claim that the large inflow of investment capital to commodity futures markets in the past decade, a phenomenon often called *financialization*, has distorted commodity prices and caused excessive volatility (Nazlioglu, Erdem, and Soytaş 2013; Cheng and Xiong 2014). According to many economists, however, little evidence supports the view that large investment inflows in commodity markets are cause for concern (Stoll and Whaley 2010; Irwin and Sanders 2011). Figure 18.1 plots commodity futures prices for oil, metals, and agricultural product between 2005 and 2016. As the figure shows, commodity futures prices experienced a boom-bust cycle between 2005 and 2016. Most commodity prices began to increase in early 2005, leading to the longest commodity price boom since the World War II. Oil prices briefly approached \$150 a barrel in July 2008 but as global demand collapsed, oil prices halved during the GFC. In searching for explanations for this pronounced cycle in commodity prices, researchers believe that the main drivers may include (1) the growing demand from emerging economies, especially China, (2) low interest rates and effective dollar depreciation, and (3) improved liquidity attributable to the growing interest of institutional investors, including hedge funds and exchange-traded funds (ETFs).

(Insert Figure 18.1 about here)

Notwithstanding the causes of this boom-bust cycle, a sudden increase in volatility in commodity prices spurred a heated debate in the literature. This chapter investigates this controversial issue by examining the level and direction of volatility transmission across three major classes of commodities: agricultural products (corn, coffee, and soybeans), energy (crude oil and gas), and metals (copper, gold, and silver). Intuitively, a better understanding of the fundamental process through which volatility transmits across the commodity markets is particularly important for investors and regulators whose strategic asset allocation decisions and policy formulation, respectively, are often influenced by the uncertainty in these markets (Chng 2009; Kang, McIver, and Yoon 2017). Moreover, to the extent that volatility is caused by trading in response to the arrival of new information to the markets (Ross 1989), a thorough assessment of volatility spillovers among commodity markets has important implications about information flows and price discovery in these markets.

The investigation of volatility linkage between commodity markets has been an expanding area for both academic and regulatory research, particularly after the GFC (Nazlioglu et al. 2013; Olson, Vivian, and Wohar 2014; Antonakakis and Kizys, 2015; Bouri 2015). For instance, using the causality-in-variance approach of Hafner and Herwartz (2006), Olson et al. (2014) investigate the relation between the energy and equity markets and show that low S&P 500 index returns cause substantial increases in the volatility of the Goldman Sachs's energy index. However, only a weak response exists from the S&P 500 volatility index to energy price shocks. Antonakakis and Kizys (2015) employ the spillover index of Diebold and Yilmaz (2012) to examine the dynamic link between returns and volatilities of commodity and currency markets. Based on weekly data between January 6, 1987 and July 22, 2014, they find that the observed transmission process is both time and event dependent. In particular, the dynamic spillover effects originating in gold and silver reach an unprecedented level during the GFC. After the GFC, however, the role of gold and silver as net transmitters of shocks weakened. Similarly, applying the newly developed causality-in-variance test and impulse response

functions, Nazlioglu et al. (2013) show that the dynamics of volatility transmission between energy and agricultural markets changes significantly following the food price crisis. Their results show that while no risk transmission exists between oil and agricultural commodity markets in the pre-crisis period, oil market volatility spills on the agricultural markets in the post-crisis period. More recently, Yaya, Tumala, and Udomboso (2016) investigate volatility persistence and returns spillovers between oil and gold markets using the Constant Conditional Correlation generalized autoregressive conditional heteroscedasticity (CCC-GARCH) modeling framework and find that oil-gold volatility spillovers exist between 1986 and 2015. However, return spillover effects switch from bidirectional before the crisis period to unidirectional (i.e., from gold to oil market) after the crisis.

However, despite the widespread attention given to this research area, the majority of studies focus on the energy-equity return relations (Arouri, Jouini, and Nguyen 2011; Olson et al. 2014; Bouri 2015), the cross-market linkages between energy and metals markets (Reboredo 2013; Yaya et al. 2016), and the volatility spillovers between energy and agricultural markets (Nazlioglu et al. 2013). Little research investigates the interrelations among the price and volatility of the three major commodity classes – agricultural products, energy, and metals. This observation is somewhat surprising given the growing concern that “financial stress is more systemic and thus more dangerous for the economy as a whole if financial instability spreads more widely across the whole system” (Holló, Kremer, and Duca 2012, p. 1). One noticeable exception is Kang et al. (2017) who examine return and volatility spillover effects among six commodity futures markets – gold, silver, West Texas Intermediate (WTI) crude oil, corn, wheat, and rice – by employing the multivariate GARCH model and the spillover index. Although Kang et al. attempt to measure the intensity and direction of volatility transmissions across the major commodity markets, they only examine six commodities between 2002 and 2016 and thus do not fully consider the changing nature volatility spillovers during the early 1990s global recession.

To address these important issues, this chapter builds on the work of Chau and Deesomsak (2014) and proposes an indicator of volatility transmission across commodity futures markets labeled the Commodity Volatility Spillover Index (CVSI) to assess interdependence in the major commodity futures markets and to identify periods of excessive spillover that may lead to global commodity price instability. Specifically, using the spillover index approach of Diebold and Yilmaz (2012), this study tracks estimates of both total and directional volatility spillovers across the energy, precious metals, and agriculture commodity markets. In contrast to other studies, this chapter directly accounts for important linkages among the major commodity futures markets in an interconnected world by considering the average and time-varying interconnectedness of each market's volatility shocks.

This chapter adds to the existing literature in several ways. First, the development of a new index of volatility spillover incorporates the important interaction and transmission of risk across the three major classes of commodities, providing investors and regulators with an early warning indicator for emergent crises. Second, the directional CVSI helps to identify the origin of systemic stress and to detect systemically important commodity markets. Finally, the conditional version of our CVSI tracks the time-varying movements and trends of both total and directional volatility spillovers. Overall, the findings of this study are important in understanding the level and transmission mechanism of risk across commodity futures markets and are relevance to regulators in formulating effective policies to tackle excessive volatility, particularly during the turbulence periods. They should also provide new insights into channels of information transmission, which may improve investment decisions and inform portfolio investors' trading strategies.

The reminder of this chapter is organized as follows. The next section describes the data and econometric modeling framework used to measure the intensity and direction of volatility transmission across different categories of commodity futures markets. Next, the main empirical

findings of this chapter are presented and analyzed. The final section summarizes and concludes the chapter.

DATA AND METHODOLOGY

This section describes the data and modeling framework of the study. It begins with a brief description of the data followed by an overview of Diebold and Yilmaz (2012)'s spillover index, which identifies dynamic volatility spillover effects across commodity futures markets.

Data Description

The data used in this chapter include the weekly observations for three categories commodity futures markets including the agricultural (CBOT corn and soybeans and ICE coffee), energy (NYMEX Brent crude oil, WTI, and natural gas), and precious metals (COMEX copper, gold, and silver). Using weekly time series data alleviates the concerns over non-synchronicities and bid-ask effects in daily data (Antonakakis and Kizys 2015; Batten, Ciner, and Lucey 2015). In particular, Wednesday closing prices of these nine globally important commodity futures markets are obtained from Thomson Reuters Datastream. The sample period is between April 4, 1990 and December 28, 2016. Unlike Kang et al. (2017), this study examines the period covering the early 1990s global recession, the more recent GFC as well as periods of economic growth. To construct a continuous series of futures prices, successive settlement rates are collected from a contract closest to expiration until the last day before the delivery month, and then switching to the next nearest contract from the first day of the delivery month. Following Lien and Shrestha (2005), the crossover returns are deleted from the data set to avoid the rollover risk when the nearby futures contract switches months.

The continuously compounded returns are calculated as logarithmic relatives $R_t = 100 \times \ln(P_t/P_{t-1})$, where P_t is the Wednesday closing futures price. Figure 18.2 displays a time-series plot of price (Panel A) and return (Panel B) movements of the nine chosen commodity futures during the sample period. Several facts emerge: (1) although the return series appear to be

stationary as expected, they fluctuate substantially over time with peaks in the periods corresponding to crisis events; (2) energy prices are generally more volatile than other commodities as indicated by the magnitude of their price movements; (3) WTI and Brent crude oil future prices increased dramatically during the GFC, and only revert to somewhat lower levels in 2009 and 2010; and (4) the prices of precious metals such as gold and silver were relatively stable before 2004 but experienced substantial growth thereafter. The growing demand for precious metals may be because investors perceive these assets as ‘safe heaven’ investments, especially in the periods of financial turmoil (i.e., the so-called ‘flight-to-quality’ phenomenon). Antonakakis and Kizys (2015) and Kang et al. (2017) document similar findings.

(Insert Figure 18.2 about here)

Table 18.1 presents the descriptive statistics of the weekly commodity futures markets returns. The statistics reported are the mean, standard deviation, measures of skewness and kurtosis, Jarque-Bera (JB) statistic, and the Ljung-Box statistic (LB) for 12 lags. Consistent with the extant literature, the futures returns series clearly depart from normality as indicated by significant JB statistics. In particular, almost all commodity futures returns are negatively skewed and slightly leptokurtic. The LB statistics provide evidence of significant temporal dependencies in the first moment of these return distributions, with the exception of soybean and silver futures. Given that the variables in the vector autoregression (VAR) must be stationary, the study tests for the presence of a unit root in these return series. In addition to the augmented Dicker-Fuller (ADF) and Phillips-Perron (PP) tests, this chapter also presents the DF-GLS unit root test proposed by Ng and Perron (2001), which has better properties than many conventional unit root tests (Elliott, Rothenberg, and Stock 1996). The test results reported in Panel B of Table 18.1 are consistent with those of Kang et al. (2017) and indicate that commodity futures returns are first-order nonstationary processes.

As an initial gauge of the dynamic interactions between commodity futures markets returns, this study estimates correlation coefficients during the sample period. The results

reported in Panel C of Table 18.1 show positive and statistically significant correlations exist among these nine commodity futures markets with corn-soybeans, gold-silver, and Brent crude oil-WTI pairs sharing the highest correlations of 0.61, 0.74, and 0.89 respectively. Nonetheless, the interaction of commodity futures may give rise to correlation patterns that are more complex than a simple correlation coefficient can capture. Thus, investigating the extent to which risk and volatility originated in one commodity market affects the others and identifying the channels through which a market's financial stress spills over across different commodity futures markets are both interesting and informative.

(Insert Table 18.1 about here)

Modeling Framework

With the rapid development of financial econometrics in the past few decades, researchers have advanced various modeling approaches to investigate the co-movements and spillovers of key financial market variables (e.g., asset return and volatility). For instance, a growing body of literature uses multivariate GARCH models to investigate return and volatility spillovers between oil market and the equity market (Arouri et al. 2011). Although multivariate GARCH models offer substantial insights in the dynamic interactions between commodity markets, the analysis in this chapter distinguishes between idiosyncratic shocks to each commodity futures market and the spillover of shocks across markets, and more importantly, identifies how shocks to each market affects other markets. In other words, the chapter uses a more advanced approach to capture how quickly volatility builds and spreads across commodity markets over time. To achieve this goal, this study follows the methodology set forth in Diebold and Yilmaz (2009, 2012) hereafter DY, generating what they term a spillover index. The spillover index is built upon the familiar notion of variance decomposition associated with an N-variable vector autoregression (VAR). The remainder of this section provides a brief overview of the DY's spillover index methodology.

Consider a covariance stationary of N-variable VAR of p^{th} -order, $x_t = \sum_{i=1}^p \Phi_i x_{t-i} + \varepsilon_t$,

where $\varepsilon_t \sim (0, \Sigma)$. In the context of current chapter, $x_t = (x_{1t}, x_{2t}, \dots, x_{nt})$ represents a vector of conditional volatility estimated by a standard GARCH (1,1) model; Φ is a $N \times N$ parameter matrix and ε is the vector of independently and identically distributed error terms with zero mean and variance of covariance matrix Σ . The moving average (MA) representation is $x_t = \sum_{i=0}^{\infty} A_i x_{t-i}$ where A_i is an $N \times N$ coefficient matrices following the recursion $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \dots + \Phi_p A_{i-p}$ with A_0 as an $N \times N$ identity matrix and $A_i = 0$ for $i < 0$. Variance decomposition allows decomposing the fraction of H-step-ahead forecast error variance into own variance shares and cross variance shares, or spillovers. The *own variance shares* refers to the part of the forecast error variance in forecasting x_i due to shocks to x_i itself for $i=1,2,\dots,N$, whereas the *cross variance shares* represent the part that is attributable to shocks from another variable x_j for $j=1,2,\dots,N$ (and $i \neq j$). Diebold and Yilmaz (2009) propose using the Cholesky-decomposition to decompose the variance. However, the Cholesky-decomposition depends on the ordering of the variables. Diebold and Yilmaz (2012) resolve this ordering problem by exploiting the generalized VAR framework of Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998), (collectively called KPPS hereafter), producing the variance decomposition invariant to ordering.

More specifically, the KPPS H-step-ahead error forecast variance decomposition is given by Equation 18.1:

$$\theta_{ij}^s(H) = \frac{\sigma_{ii}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)} \quad (18.1)$$

where Σ represents the variance matrix for error vector ε ; σ_{ii} is the standard deviation of the error term for i^{th} equation; and e_i is the selection vector with one for the i^{th} element and zero otherwise. Unlike Cholesky factor orthogonalization, the KPPS H-step-ahead error forecast

variance decomposition does not try to orthogonalize the shock but instead allows for correlated shocks and accounts for them appropriately using the historical distribution of the errors.

However, as Diebold and Yilmaz (2012, p. 58) state, “As the shocks to each variable are not orthogonalized, the sum of contributions to the variance of forecast error (that is, the row sum of the elements of the variance decomposition table) is not necessarily equal to one.” Thus, each entry of the variance decomposition matrix in Equation 18.1 must be normalized to use the information from the variance decomposition matrix.

Equation 18.2 shows the normalization of the entry for the variance decomposition matrix by the row sum:

$$\tilde{\theta}_{ij}^g(H) = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^N \theta_{ij}^g(H)} \quad (18.2)$$

where $\sum_{j=1}^N \tilde{\theta}_{ij}^g(H) = 1$ and $\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H) = N$.

Using the normalized entry for the generalized variance decomposition matrix in Equation 18.2, Diebold and Yilmaz construct the total spillover index as Equation 18.3:

$$S^g(H) = \frac{\sum_{i,j=1, i \neq j}^N \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H)} \times 100 = \frac{\sum_{i,j=1, i \neq j}^N \tilde{\theta}_{ij}^g(H)}{N} \times 100 \quad (18.3)$$

Besides the total spillover index, information from KPPS variance decomposition also enables measuring the directional spillovers across the markets in order to understand how shocks to the commodity markets are carried across and transferred among the major commodity assets. In particular, Equation 18.4 shows how the directional spillover received by market i from all other markets j can be calculated:

$$S_{i\bullet}^g(H) = \frac{\sum_{j=1, i \neq j}^N \tilde{\theta}_{ij}^g(H)}{\sum_{j=1}^N \tilde{\theta}_{ij}^g(H)} \times 100 \quad (18.4)$$

Similarly, the directional spillover transmitted by market i to all other markets j can be measured as shown in Equation 18.5:

$$S_{\bullet i}^g(H) = \frac{\sum_{j=1, i \neq j}^N \tilde{\theta}_{ji}^g(H)}{\sum_{j=1}^N \tilde{\theta}_{ji}^g(H)} \times 100 \quad (18.5)$$

Finally, obtaining the net directional spillover from market i to all other markets j involves calculating the difference between Equations 18.4 and 18.5 and as shown in Equation 18.6:

$$S_i^g(H) = S_{\bullet i}^g(H) - S_{i\bullet}^g(H) \quad (18.6)$$

This net directional spillover provides critical information about how much (in net terms) each of the commodity futures market contributes to volatility transmission within the overall system.

International financial markets have become increasingly interconnected because of the advances in technology and increasing globalization. Financial events in any part of the world now influence every part of the world. Although this interconnectedness has created opportunities for improving efficiency, it also has the potential to amplify financial shocks and spark contagion across marketplaces globally. The GFC highlights this risk as the collapse of one financial institution rippled through markets worldwide, affecting thousands of financial firms and ultimately threatening global financial stability (Diebold and Yilmaz 2012). The generality of the DY's spillover measures (both total and directional) is often useful allowing for identification of the main transmitters and recipients of shocks in such a globalized financial world. The next section uses these spillover results to derive some intuitive measures of volatility spillovers, called the Commodity Volatility Spillover Index (CVSI). The chapter then uses the CVSI to study the levels and trends of volatility interdependence in the major commodity futures markets – including energy, precious metals, and agriculture commodity assets. Antonakakis and Kizys (2015) and Kang et al. (2017) provide further discussion about the empirical advantages of DY's method.

EMPIRICAL FINDINGS

To investigate the level and direction of volatility transmission across the major classes of commodities, this study uses the generalized VAR framework of Diebold and Yilmaz (2012) to construct total and directional net spillovers. This section presents the estimation results of a nine-variate VAR incorporating the GARCH(1,1) volatility estimates of nine commodity futures (i.e., corn, coffee, soybean, brent oil, WTI, natural gas, copper, gold, and silver). Then, in an attempt to check the sensitivity of estimation results, it reports several robustness tests results.

Volatility Linkage and Transmission Mechanism

The previous section illustrates how the Diebold and Yilmaz (2012) spillover index framework can be used to construct an indicator of volatility transmission to monitor the levels of stress spillovers across major commodity markets. This section presents both total and directional spillover indices and examines their time-series dynamics over the sample period. Two associated tools of DY's methodology are spillover tables and spillover plots. However, as DY emphasize, while a spillover table provides a useful summary of the total (i.e., average) spillover behavior over the whole sample, this point estimate is a static measure that, by definition, cannot capture the secular and cyclical movements in spillovers. In fact, changes in spillovers are particularly important when examining turbulence in the commodity markets and how dynamics in commodity markets evolve. Thus, besides reporting the unconditional full-sample spillover table, this chapter also presents the time-varying conditional spillover plots to assess the nature and direction of volatility spillover variation over time.

Unconditional Full-sample Volatility Spillover

Following Diebold and Yilmaz (2012), this study applies a second-order VAR with 10-step-ahead forecasts to do the generalized variance decomposition of conditional volatility of nine major commodity futures markets including the agricultural (corn, coffee, and soybeans), energy (Brent crude oil, WTI, and natural gas), and precious metals (copper, gold, and silver). As a robustness check, the chapter also calculates the total spillover indices for a fourth-order VAR

with five-step forecast horizons. As reported in the robustness tests section, the results show that the levels of spillover are similar, irrespective of the choices of order of VAR or the forecast horizon. Table 18.2 provides the average levels of both total and directional spillovers over the full-sample period. The off-diagonal column sums, which are labelled 'Contribution to others', and row sums, which are labelled 'From others' are the 'TO' and 'FROM' directional spillovers, and 'TO-FROM' differences are the net directional spillovers. The lower corner of the table reports the total spillover index.

As Table 18.2 shows, the total financial stress spillover is not sizeable (the total spillover index is 24.8 percent), indicating that, on average, over the sample period between April 11, 1990 and December 28, 2016, the cross-market volatility spillovers explain less than a quarter of the variations in these major commodity futures markets, while idiosyncratic shocks to individual commodity market volatility levels explain the remaining 75.2 percent variations. These results are directly comparable to that of Antonakakis and Kizys (2015) and Kang et al. (2017). In terms of the directional spillovers transmitted TO others, global oil price volatility as measured by the two major categories of crude oil (i.e., Brent oil (45.7 percent) and WTI (43.3 percent)) appears to be the largest average contributor to volatility spillovers in other commodity futures markets, followed by silver (35.8 percent) and gold (33.4 percent). Interestingly, judging by the directional spillovers received FROM others, these energy and metal markets are also the largest recipients of volatility spillovers from others with Brent oil, WTI, silver, and gold receiving 45.0 percent, 45.4 percent, 31.3 percent, and 30.0 percent, respectively. In contrast, coffee barely transmits any financial volatility to other commodity markets and coffee does not receive any volatility spillovers from other markets. The net directional spillovers (TO – FROM) confirms that agricultural markets (corn, coffee, and soybeans) are generally the net recipient of commodity volatility spillover. Silver (4.5 percent) and gold (3.4 percent), conversely, are the net transmitters of volatility. The results also indicate that natural gas is the most exogenous market

because 97.8 percent of natural gas market variations are due to volatility shocks generated in its market.

(Insert Table 18.2 about here)

These findings are consistent with the results of previous studies showing that precious metals (e.g., silver and gold) play an important role in the development of risk and uncertainty in the financial system (Antonakakis and Kizys 2015; Batten et al. 2015). According to a survey conducted by O'Connor, Lucey, Batten, and Baur (2015), silver and gold are closely associated throughout history and can be treated as 'safe havens' or hedges against stocks and bonds in times of panic and extreme market stress. Thus, the market often interprets the unanticipated increases in the price of these precious metals as a signal of future adverse conditions and uncertainty producing sharp movements in the global commodity prices. Despite these concerns, the results raise an important question on whether the 'scapegoating' of one particular asset (e.g., gold or silver) can help policymakers reach reliable policy conclusions. On the contrary, this chapter contends that focusing on one particular market might serve to distract regulatory attention from the central problems inherent in the operations and interconnectedness of the global commodity market as a whole. The call for further regulation on trading of these commodity futures markets, such as higher margins, narrower fluctuation limits, and restrictions on the issue of contracts may not be fully justified.

Despite this advised caution, regulators have historically reacted to market volatility with these precise measures. For instance, on August 11, 2011, the world's largest gold futures market, Chicago Mercantile Exchange (CME), raised the margins on its gold futures by 22 percent, effectively reducing the demand for gold and associated volatility. This change was not an isolated event as Shanghai Gold Exchange (SGE) also raised its margin requirements on gold to 11 percent in the same month.

Conditional Time-varying Stress Spillover

In this section, this study calculates the conditional spillover indices by re-estimating the second-order VAR weekly, using a 200-week rolling estimation window, which is roughly four years of weekly data, to assess the time-varying nature of both total and directional volatility spillovers. This study also checks the sensitivity of the findings to the 200-week estimation window by replicating results with a 100-week rolling estimation window.

Figure 18.3 presents the conditional total volatility spillover plot. Several important observations can be drawn from this figure. First, as expected, the spillover index varies considerably over time. Starting at a value of around 38 percent in the first window, the spillover index fluctuates mostly between 30 and 40 percent. However, during the onsets of the GFC and Eurozone debt crisis, the cross-market volatility spillovers show very sharp jumps and exceed the 50 percent mark during 2010 and 2011. Second, although the index fluctuates over time, Figure 18.3 allows differentiation between several cycles, typically corresponding to the GFC and the food crisis. Lastly, the spillover index also tends to increase rapidly during the beginning periods marked as recessions. Examination of how the intensity of commodity volatility spillovers affects the overall economic activity and the evolution of financial crises is worthy of further study, but is beyond the scope of this chapter.

(Insert Figure 18.3 about here)

Besides the conditional total spillover plot, this chapter also presents the time-varying directional spillover plots in order to allow policymakers to derive an early-warning system for identifying the 'origin' of stress. These basic measures should assist policymakers in taking appropriate regulatory actions as necessary. This study focuses on the net directional spillover plots presented in Figure 18.4 to demonstrate the time-varying differences between directional TO and directional FROM spillovers (i.e., $TO - FROM$) for each commodity futures market. Consistent with the unconditional findings reported in Table 18.2, these time-series plots are quite revealing about the net spillovers of energy and metal markets to others. The high net spillovers from crude oil to other markets are most evident after the 2000s, around the

European debt crises, and the intensification of the GFC. The gold market was also an important source of commodity volatility spillovers with its net spillovers reaching almost 40 percent around the burst of dot-com bubble. However, since late 2003, its role was reversed and gold received almost 20 percent of volatility from other markets in 2006. The agricultural futures markets, conversely, were the net recipient of commodity volatility spillovers over most of the sample period.

(Insert Figure 18.4 about here)

Taken together, the evidence thus far suggests that important volatility episodes and fluctuations exist across major commodity markets; the total cross-market spillovers were limited until the onsets of GFC. As the crisis intensified, so too did the commodity volatility spillovers with much stress carrying over from the energy and metal markets to others. These findings are important in understanding the level and transmission mechanism of financial stress across the major commodity markets and are relevant to the market regulators in formulating effective policies to tackle financial stress transmission, particularly during turbulent periods.

Robustness Tests

To check the sensitivity of these base results, this study re-estimates and plots the total volatility spillover indices based on (1) five-week forecast horizon, (2) a fourth-order VAR model, and (3) a 100-week rolling window. The figures presented in Figure 18.5 show that the total spillover plot is insensitive to the choices of forecast horizon, order of VAR model or the estimation window size. The spillover indices appear to follow similar patterns. Several previous studies carry out similar robustness checks (Antonakakis and Kizys 2015; Kang et al. 2017).

(Insert Figure 18.5 about here)

SUMMARY AND CONCLUSIONS

Commodity futures markets have witnessed staggering growth since the early 2000s.

Commodity futures have become a popular asset class for institutional investors, just like stocks

and bonds. This phenomenon is sometimes called the financialization of commodity markets. In fact, the observed steep rises in the commodity prices and volatility has spurred a heated debate in both public and policy circles as to whether financialization of commodity markets destabilised commodity futures markets. Moreover, the debate among policymakers has culminated in questions about the need for more government regulation in these markets.

This chapter examines this controversial topic, investigating the intensity and direction of volatility transmission across three major classes of commodities including agricultural products (corn, coffee, and soybeans), energy (crude oil and gas), and metals (copper, gold, and silver). To this end, this chapter develops an indicator of volatility transmission across commodity futures markets, the Commodity Volatility Spillover Index (CVSI), to better understand the current state of market instability and to provide regulators with an early warning system for emergent crises. Building on the work of Diebold and Yilmaz (2012) and Chau and Deesomsak (2014), this study derives several conditional and unconditional measures capturing both level and transmission mechanism of volatility across the nine major commodity futures markets.

The evidence points to important stress episodes and fluctuations in volatility spillovers across markets over time; the total cross-market stress spillovers are limited until the onsets of various global crises. As crises intensify, so too do the financial stress spillovers, with considerable stress generally carrying over from energy and metal markets to other commodity futures markets. These results also reveal that coffee and natural gas are exogenous markets that barely transmit any volatility to, or receive volatility spillovers from, other commodity futures markets.

Overall, these findings provide clear evidence on the importance of crude oil and gold in ensuring global commodity market stability. In this light, crude oil and gold are of great importance to the regulatory authorities and policymakers who have a responsibility of safeguarding market stability and promoting economic growth. However, the evidence shows that interconnectedness in the modern world has substantially increased the complexity and

fragility of the commodities network. Although crude oil and gold markets provide important signals of economic instability, scapegoating one particular sector (e.g., oil or gold) for the collapse of commodity prices might not be optimal in reaching reliable policy conclusions. On the contrary, focusing on crude oil and gold market regulation may distract regulatory attention from other central problems inherent in the operations and interconnectedness of the global commodity market as a whole. In this light, the claim for further regulation on these specific commodity futures markets, such as higher margins and narrower fluctuation limits, may not be justified.

Several important directions for future research exist, both substantive and methodological. Substantive research should include an examination of how the intensity of commodity volatility spillovers affects the overall economic activity and the evolution of financial crises. Further research could also examine the volatility spillovers within a certain commodity class (e.g., precious metals) as well as other asset classes and multiple asset classes in order to provide additional insights into the linkages and interconnectedness among the global financial markets. On the methodological front, the modeling framework adopted in this chapter can be extended by providing a comparative assessment of our volatility spillover indicator (CVSI) against those generated by other methods such as multivariate-GARCH model and the causality-in-variance approach of Hafner and Herwartz (2006). Besides, structural breaks may exist in the dynamic volatility spillovers over a long time period and extending the Diebold and Yilmaz (2012)'s spillover index approach to a Markov-switching framework would be an interesting area for future research.

DISCUSSION QUESTIONS

1. Identify the three major classes of commodities.
2. Explain the term “financialization of commodity markets.”
3. Identify three main reasons for the boom and bust in commodity prices.

4. Identify which commodity futures markets are the largest contributors (recipients) of volatility spillovers to (from) others between 1990 and 2016.

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Table 18.1 Descriptive Statistics of Commodity Futures Returns

This table reports the sample mean, standard deviation, skewness, and kurtosis for the commodity futures returns. JB is the Jarque-Bera test for normality and LB(12) is the Ljung-Box Q test of serial correlation. The unit root tests include a constant term, with lag length determined by the Schwartz Information Criteria. Critical values for ADF, PP, and DF-GLS tests are from Mackinnon (1996). *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively.

	Corn	Coffee	Soybeans	Brent Oil	WTI	Natural Gas	Copper	Gold	Silver
Panel A. Summary statistics									
Mean	0.019	0.024	0.038	0.081	0.072	0.041	0.052	0.079	0.081
Standard deviation	3.781	5.291	3.252	4.730	4.951	7.485	3.466	2.255	3.977
Skewness	-0.146	0.531	-0.497	-0.568	-0.341	0.172	-0.274	-0.312	-0.604
Kurtosis	5.523	7.615	5.550	8.060	7.029	5.416	5.475	7.468	7.283
JB	374.857 ***	1303.640 ***	435.596 ***	1563.524 ***	970.464 ***	346.095 ***	373.490 ***	1182.888 ***	1151.190 ***
LB(12)	20.836 *	41.152 ***	16.097	22.33 **	40.246 ***	34.492 ***	35.368 ***	28.506 ***	16.732
Panel B. Unit root tests									
ADF	-38.823 ***	-40.225 ***	-24.571 ***	-38.922 ***	-20.546 ***	-40.531 ***	-24.501 ***	-37.238 ***	-37.951 ***
PP	-38.793 ***	-40.245 ***	-37.665 ***	-39.031 ***	-38.954 ***	-40.527 ***	-38.507 ***	-37.589 ***	-38.209 ***
DF-GLS	-8.339 ***	-40.217 ***	-24.376 ***	-2.616 ***	-2.709 ***	-6.849 ***	-6.152 ***	-5.728 ***	-36.285 ***
Panel C. Correlation coefficients									
Corn	1								
Coffee	0.1576 ***	1							
Soybeans	0.6074 ***	0.1645 ***	1						
Brent oil	0.1515 ***	0.0897 ***	0.1903 ***	1					
WTI	0.1300 ***	0.0953 ***	0.1729 ***	0.8867 ***	1				
Natural gas	0.0920 ***	0.0342	0.1017 ***	0.2045 ***	0.2200 ***				
Copper	0.1669 ***	0.1320 ***	0.2071 ***	0.2461 ***	0.2526 ***	0.0501 *	1		
Gold	0.1710 ***	0.1381 ***	0.1690 ***	0.2485 ***	0.2342 ***	0.0579 **	0.2909 ***	1	
Silver	0.2000 ***	0.1919 ***	0.2114 ***	0.2516 ***	0.2417 ***	0.0879 ***	0.3529 ***	0.7441 ***	1

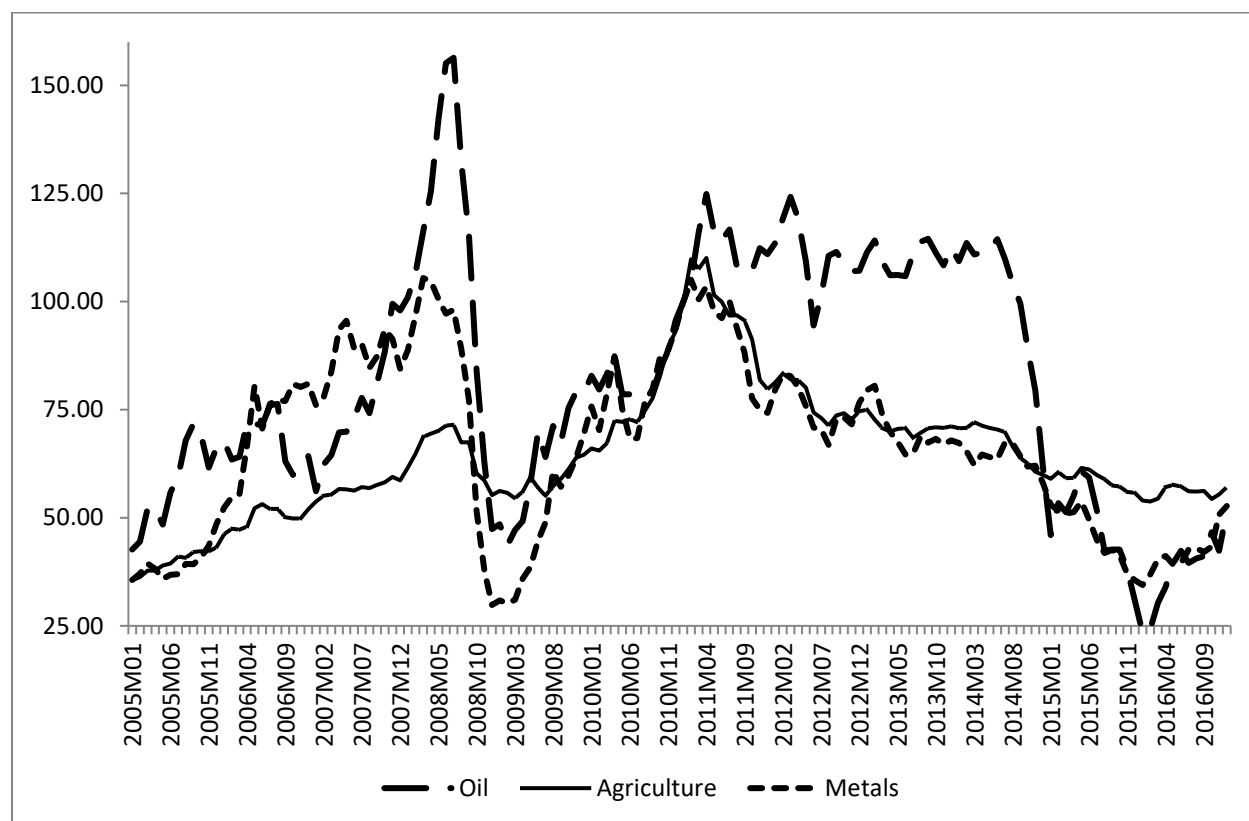
Table 18.2 Volatility Spillover Table, Commodity Futures Markets: Full Sample

This table reports the full sample (i.e. average) total and directional volatility spillovers. The second-order VARs with 10-step-ahead forecasts are used to do the generalized variance decomposition for nine major commodity futures markets. The off-diagonal column sums (labelled 'Contribution to others') and row sums (labelled 'From others' are the 'TO' and 'FROM' directional spillovers, and 'TO-FROM' differences are the net directional spillovers. The total spillover index is given in the lower corner of the table.

	Corn	Coffee	Soybeans	Brent Oil	WTI	Natural Gas	Copper	Gold	Silver	From Others
Corn	76.44	0.16	15.06	0.02	0.14	0.84	4.21	1.09	2.03	23.60
Coffee	0.09	94.59	0.39	0.84	0.16	1.22	0.93	0.61	1.17	5.40
Soybeans	18.71	0.26	76.37	0.04	0.32	0.88	2.01	0.29	1.12	23.60
Brent oil	0.11	0.07	0.48	55.02	38.33	0.96	1.22	2.14	1.69	45.00
WTI	0.18	0.02	0.24	39.85	54.57	0.38	0.83	2.59	1.35	45.40
Natural gas	0.40	0.12	0.10	0.14	0.16	97.79	0.83	0.13	0.33	2.20
Copper	0.87	0.24	0.38	2.58	2.56	0.10	83.52	3.21	6.56	16.50
Gold	1.05	0.61	1.40	1.19	1.16	0.10	3.02	69.96	21.52	30.00
Silver	1.17	0.31	1.79	1.03	0.47	0.06	3.08	23.39	68.71	31.30
Contribution to others	22.60	1.80	19.80	45.70	43.30	4.50	16.10	33.40	35.80	223.00
Contribution incl. own	99.00	96.40	96.20	100.70	97.90	102.30	99.60	103.40	104.50	Spillover
Net spillovers (TO – FROM)	–1.00	–3.60	–3.80	0.70	–2.10	2.30	–0.40	3.40	4.50	Index = 24.8%

Figure 18.1 Commodity Price Movements between 2005 and 2016

The figure shows commodity futures prices for crude oil, metals, and agricultural materials between 2005 and 2016 (US\$, January 2011 = 100).

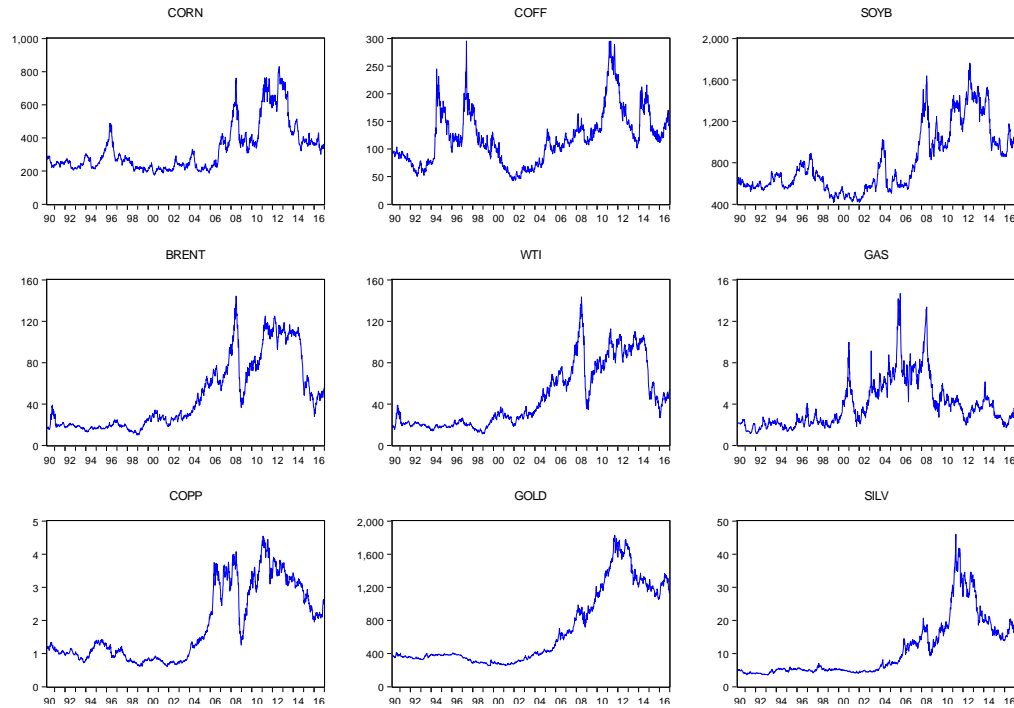


Source: The World Bank.

Figure 18.2 Time-series Plot of Commodity Futures Markets Movements

The figure shows a time-series plot of the price (Panel A) and return (Panel B) movements of nine commodity futures markets during the sample period between April 4, 1990 and December 28, 2016.

Panel A. Commodity futures price



Panel B. Commodity futures return

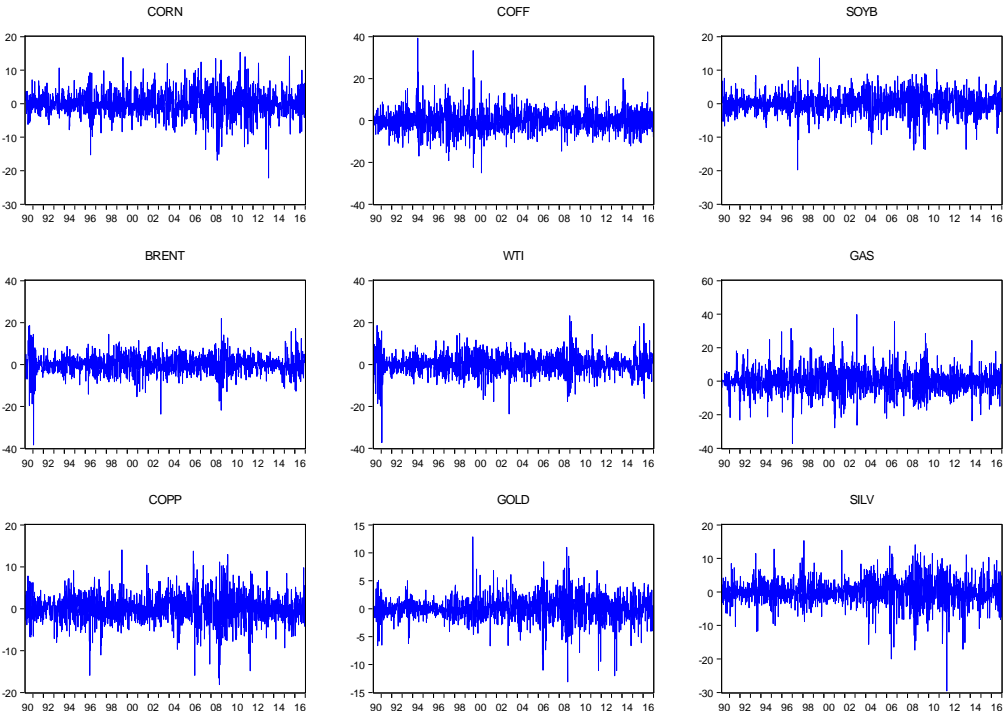


Figure 18.3 Time-varying Volatility Spillover across Commodity Futures Markets

This figure shows the total volatility spillover across nine major commodity futures markets. The values are calculated by re-estimating the second-order VAR, using a 200-week rolling estimation window with a 10-week forecast horizon. Generalized variance decomposition method is used. The sample period is between April 11, 1990 and December 28, 2016.

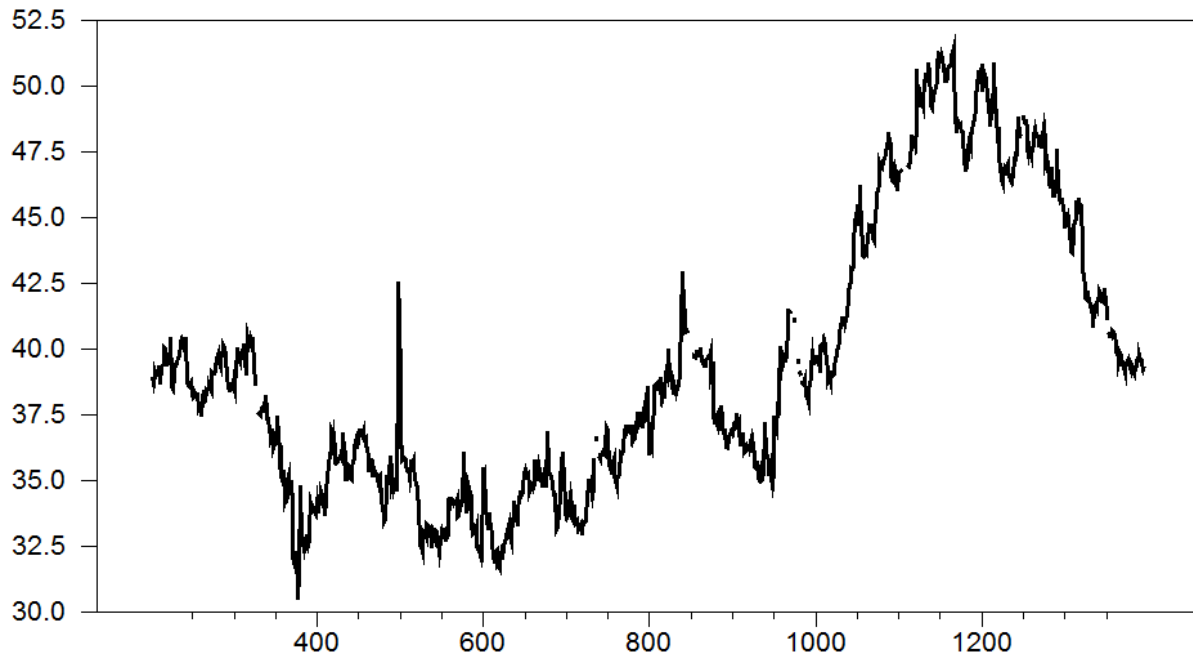


Figure 18.4 Net Volatility Spillovers across Commodity Futures Markets

This figure shows the net volatility spillover across nine major commodity futures markets. The values are calculated by subtracting directional 'TO' from directional 'FROM' spillovers. Positive (negative) values of the net spillover suggest that the market is a net transmitter (receiver) of volatility spillovers. The second-order VAR is employed using a 200-week rolling estimation window with 10-week forecast horizon. The sample period is between April 11, 1990 and December 28, 2016.

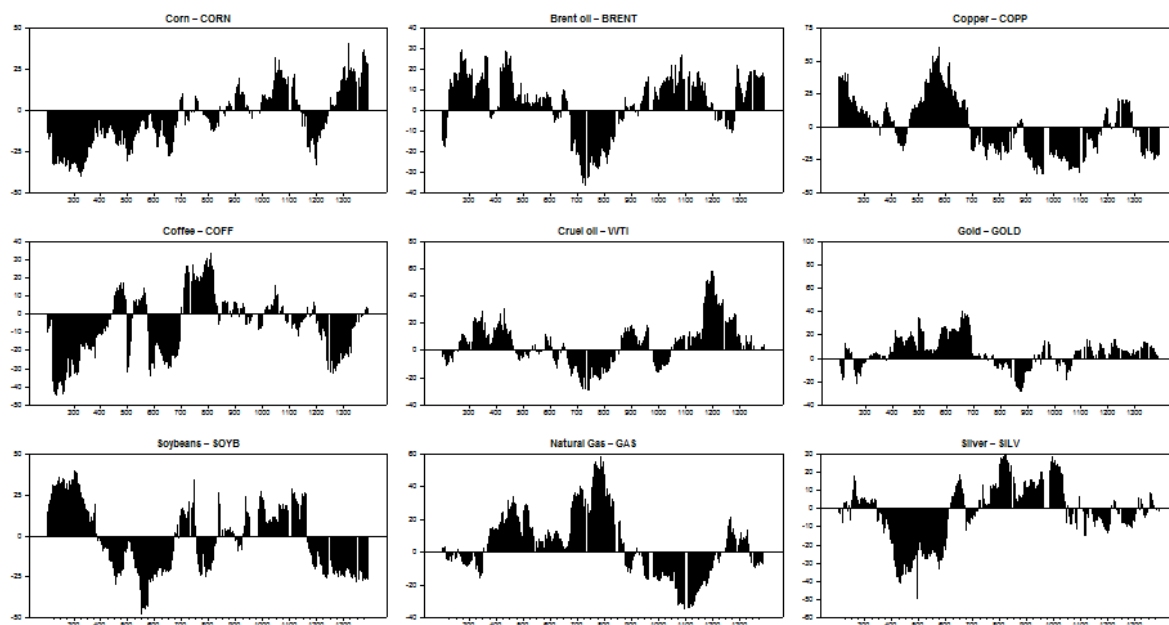
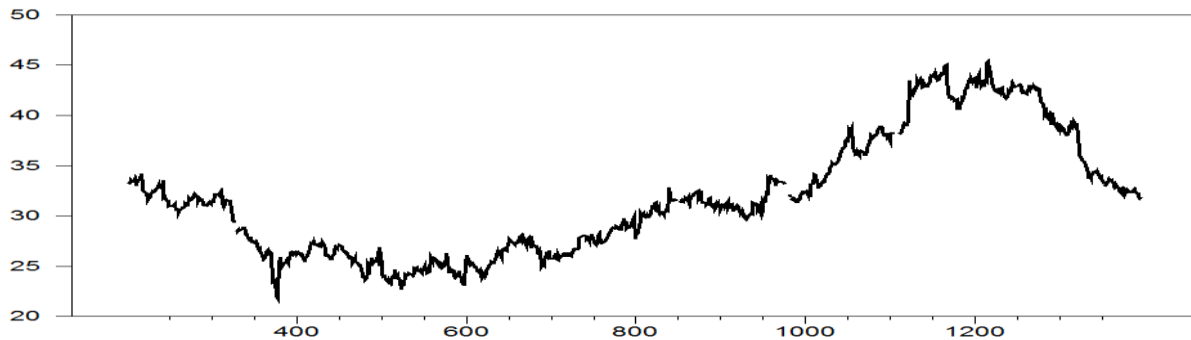


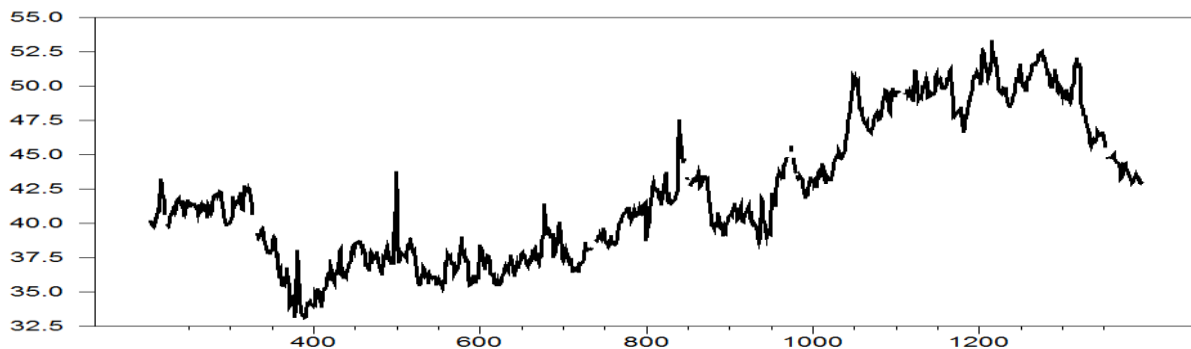
Figure 18.5 Robustness Tests

These figures show the total volatility spillover indices calculated by re-estimating using (1) the second-order VAR, using a 200-week rolling estimation window with five-week forecast horizon (Panel A), (2) the fourth-order VAR, using a 200-week rolling estimation window with 10-week forecast horizon (Panel B), and (3) the second-order VAR, using a 100-week rolling estimation window with 10-week forecast horizon (Panel C).

Panel A. Total volatility spillover, second-order VAR, 200-week rolling window, five-week forecast horizon



Panel B. Total volatility spillover, fourth-order VAR, 200-week rolling window, 10-week forecast horizon



Panel C. Total volatility spillover, second-order VAR, 100-week rolling window, 10-week forecast horizon

